A Machine Learning Technique for MRI Brain Images

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***Abstract*- This study presents a proposed hybrid intelligent machine learning technique for Computer–Aided detection system for automatic detection of brain tumor through magnetic resonance images. The technique is based on the following computational methods; the feedback pulse-coupled neural network for image segmentation, the discrete wavelet transform for features extraction, the principal component analysis for reducing the dimensionality of the wavelet coefficients, and the feed forward backpropagation neural network to classify inputs into normal or abnormal. The experiments were carried out on 101 images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The classification accuracy on both training and test images is 99 % which was significantly good. Moreover, The proposed technique demonstrates its effectiveness compared with the other machine learning recently published techniques.**

Keywords:* *MRI brain imaging, Computer-aided detection, Medical Informatics, Machine learning, Image Processing, Computational Intellegence

I. INTRODUCTION

Brain tumor is one of the most common major causes for the increase in Mortality among children and adults in the world. A tumor is a mass of tissue that grows out of control of the normal forces that regulate growth. Most Research in developed countries show that the number of people who develop brain tumors and die from them has increased perhaps as much as 300 over past three decades. The overall annual incidence of primary brain tumors in the U.S is 11 to 12 per 100,000 people for primary malignant brain tumors, that rate is 6 to 7 per 1,00,000. In the UK, over 4,200 people are diagnosed with a brain tumor every year [1]. Early detection of the brain tumor is very important. In the brain Magnetic Resonance Imaging (MRI), the tumor may appear clearly but for further treatment, the physician also needs the quantification of the tumor area. The computer and image processing techniques can provide great help in analyzing the tumor area [5].

On the other side, computer-aided detection (CAD) has been developing fast in the last two decades. The main idea of CAD is to assist radiologists in interpreting medical images by using dedicated computer systems to provide ‘second opinions’. The final medical decision is made by the radiologists. Studies on CAD systems and technology show that CAD can help to improve diagnostic accuracy of radiologists, lighten the burden of increasing workload, reduce cancer missed due to fatigue, overlooked or data overloaded and improve inter- and intra-reader variability [2, 5]. Recently, various types of brain Computer-Aided Detection (CAD) methods have been developed by a number of researchers, including our group, using brain MR images based on several types of machine learning classifiers. In general, there are two types of CAD systems for brain evaluation (i.e., systems that detect lesions and those that differentiate diseases). Brain CAD systems can provide radiologists with a 'second opinion' to assist them in the detection of brain diseases. Consequently, radiologists expect that CAD systems can improve their diagnostic abilities based on synergistic effects between the radiologist and the computer with medical image analysis and machine learning techniques. Therefore, the CAD systems should have abilities similar to the radiologists in terms of learning and recognition of brain diseases. For this reason, pattern recognition techniques including machine learning play important roles in the development of CAD systems [3]. Pattern recognition is the act of extracting features from objects (e.g. lesions) in raw data and making a decision based on a classifier output, such as classifying each object into one of the possible categories of various patterns.

The organization of the paper is as follows. Section 2 presents the technique methodology with a short description for its four phases: defining the ROI, feature extraction and reduction, and classification, Section 3 presents the experiment results and discussion and Section 4 presents the conclusion.

II. THE PROPOSED METHODOLOGY

The architecture for the CAD Brain MRI system is shown in Figure 1. It comprises four main processes for (i) Image Acquisition, (ii) Segmentation of ROI, (iii) Feature Extraction and Selection, and (iv) Classification of the selected ROI. Image acquisition techniques like magnetic resonance imaging (MRI), X-Ray, ultrasound, mammography, CT-scan are highly dependent on computer technology to generate digital images. After obtaining digital images, image processing techniques can be further used for analysis of region of interest.

A. Defining Region of Interest

Image segmentation and defining the region of interest (ROI) is an important approach and the most time-consuming part of image analysis and processing, which can divide the images into different parts with certain distinctions. The most valid and effective method is threshold segmentation based on gray-scale. It is the key point of image segmentation, that is, how to select the suitable threshold in order to realize the correct segmentation—which makes binary image neither to produce under-segmentation, nor over-segmentation.

In this paper we used Feedback Pulse-Coupled Neural network (FPCNN) which is a modification of Pulse-Coupled Neural Network (PCNN) [4]. PCNN is considered a very powerful front-end processor for an image recognition system. It's based on the biological version of a pre-processor. It has the ability to extract edge information, texture information, and to segment the image. This type of information is extremely useful for image recognition engines. One of the best advantages of PCNN over the previous image segmentation algorithms is being very generic. Very few changes (if any) to the PCNN are required to operate on different types of data. In spite of other image segmentation techniques which require information about the target before they are effective [6]. The PCNN applied to the processing of images of heterogeneous materials; specifically PCNN is applied to image smoothing, image denoising, image segmentation and edge extraction.

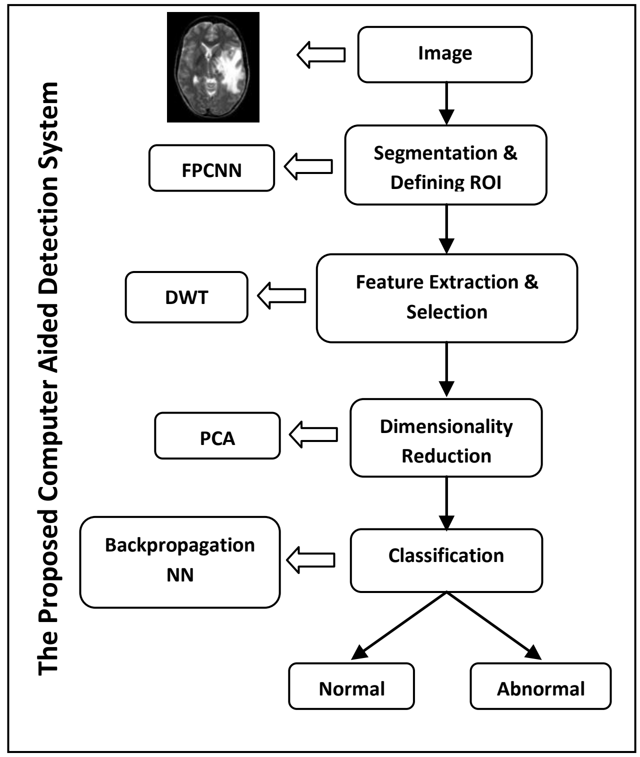

Figure 1. the proposed methodology of CAD Brain MRI system

The PCNN based image segmentation process for defining the Region of Interest (ROI) can be viewed as a region growing method where seed pixels are identified by the neurons that fire during primary firing and the region growing is accomplished by capturing spatially connected neighboring neurons through secondary firing. PCNN, called the third generation artificial neural network, as shown in Figure 2. is feedback network formed by the connection of lots of neurons, according to the inspiration of biologic visual cortex pattern. Every neuron is made up of three sections: receptive section, modulation and pulse generator section, which can be described by discrete equations.

$$F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{kl} M_{ijkl} Y_{kl}[n-1] + I_{ij} \quad (1)$$

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} W_{ijkl} Y_{kl}[n-1] \quad (2)$$

$$U_{ij}[n] = F_{ij}[n]\left(1 + \beta L_{ij}[n]\right) \quad (3)$$

$$Y_{ij}[n] = \begin{cases} 1, \left(U_{ij}[n] > \theta_{ij}[n]\right) \\ 0, \left(U_{ij}[n] \le \theta_{ij}[n]\right) \end{cases} \quad (4)$$

$$\theta_{ij}[n] = e^{-\alpha_\theta} \theta_{ij}[n-1] + V_\theta Y_{ij}[n] \quad (5)$$

Equations (1) - (5) describe the PCNN neurons. i, j are the neuron markings , n is the iterations, I is neurons external stimulation, F is feedback input, L is connecting input, U is internal activity items, θ is dynamic threshold;

M and W are connection weight matrixes (typically M = W); V_F, V_L, V_θ are amplitude constants for F, L, θ respectively; V_F, V_L, V_θ third party $\propto_F$, $\propto_L$, α_θ are corresponding attenuation coefficients respectively; β is the weak connection (linking) coefficient; Y is PCNN binary output.

The PCNN produces a dynamic output that contains edge, texture and segmentation information at different times. This is performed by continual iterations of the input and output signals using the Equations (1) – (5).

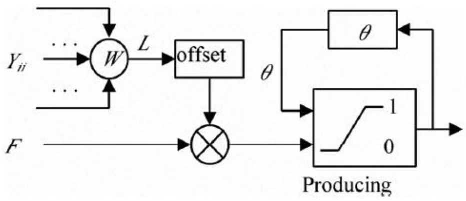

Figure 2. PCNN Basic Model. The model has three main parts: the receptive fields, the modulation product, and the pulse generator.

For the Feedback PCNN (FPCNN), the outputs are collected as a weighted time average, A, in a fashion similar to the computation of θ except for a the constant V,

$$A_{ij}[n] = \exp(-\alpha_A)A_{ij}[n-1] + V_A Y_{ij}[n] \qquad (6)$$

where V_A is much lower than V. In our case, V_A = 1.

The input is then modified by,

$$I_{ij}[n] = \frac{I_{ij}[n-1]}{A_{ij}[n-1]} \qquad (7)$$

The FPCNN iterates the PCNN Equations (1) - (5) with (6) and (7) inserted at the end of each iteration [6, 9].

B. Feature Extraction

In this paper, the feature extraction of MRI images is obtained using the discrete wavelet transform (DWT) domain subimages. The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficient from MR images. The DWT is implemented using cascaded filter banks in which the lowpass and highpass filters satisfy certain specific constraints. The basic scheme of DWT decomposition and its application to MR images is shown in Figure 3. where the functions h(n) and g(n) represent the coefficients of the high-pass and low-pass filters, respectively.

As a result, there are four sub-band (LL, LH, HH, HL) images at each scale. The LL subband can be regarded as the approximation component of the image, while the LH, HL, HH subbands can be regarded as the detailed components of the image. For feature extraction, only the subband LL is used for DWT decomposition at next scale. Also, the LL subband at last level is used as output feature vector. In our algorithm, a two level decomposition via Haar wavelet was utilized to extract features.

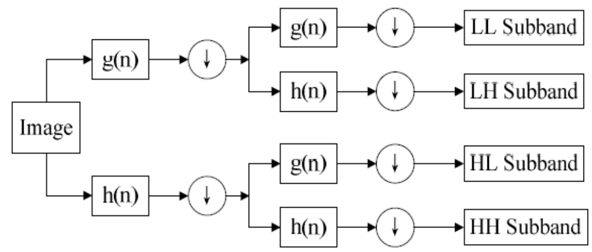

Figure 3. a schematic diagram of 2D wavelet transform decomposition

C. Feature Reduction

Excessive features increase the computation time and memory storage which sometimes causes some complications in the classification process (the curse of dimensionality), and so it's required to reduce the number of features. The principal component analysis (PCA) is the most well-known used subspace projection technique as it provides suboptimal solution with a low computational cost and computational complexity. PCA is an efficient strategy for transforming the existing input features of a data set consisting of a large number of interrelated variables into a new lower-dimension feature space while retaining most of the variations. The input feature space is transformed into a lower-dimensional feature space using the largest eigenvectors of the correlation matrix and forms a new set of ordered variables according to their variances or their importance [7,8].

This technique has three effects: it orthogonalizes the components of the input vectors so that uncorrelated with each other, it orders the resulting orthogonal components so that those with the largest variation come first, and eliminates those components contributing the least to the variation in the data set. Using a system of feature reduction based on PCA limits the feature vectors to the component selected by the PCA which leads to an efficient classification algorithm. So, the main idea behind using PCA in our approach is to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier [8,9].

D. MRI image Classification

Neural networks are widely used in pattern classification since they do not need any information about the probability distribution and the a priori probabilities of different classes. For brain MR image classification, as normal or abnormal, we used a Backpropagation Neural Network (BPNN) to classify inputs into the set of target categories (normal or abnormal) based on feature selection parameters. BPNN is a supervised learning method which is a non-linear generalization of the squared error gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron, generalized to feed-forward networks [10]. The network configuration is N_I * N_{H1} * 1, such that a three-layer network with 7 input neurons for the feature vectors selected from the wavelet coefficients by the PCA, 5 neurons in the hidden layer and single neuron in the output layer was used to represent normal and abnormal human brain.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed technique was developed in MATLAB version 7.10.0 using combination of the PCNN Toolbox, Wavelet Toolbox and Neural Network Toolbox running under windows-7 operating system.

A. Database

The algorithm were implemented based on 101 brain MRI images consisting of 14 normal and 87 abnormal (malignant and benign tumors) from a real human brain MRI dataset. The dataset used consists of axial, T2-weighted, 256-256 pixel MR brain images. These images were collected from the Harvard Medical School website (http:// med.harvard.edu/AANLIB/) [11]. Figure 4. shows some sample images from the data set used for normal and abnormal brain images: (a)Normal, (b)Meningioma, (c)Metastatic bronchogenic carcinoma, (d)Glioblastoma, (e)Alzheimer's disease, (f)Alzheimer's disease with visual agnosia, (g)Sarcoma, (h)Glioma.

The images were randomly selected as there are one type of normal brain and 11 different types of abnormal brain in the dataset 7 types of them where named previously, total 101 images consisting of 14 normal and 87 abnormal brain images.

TABLE I. SETTING OF TRAINING AND TEST IMAGES

Total No. of images	No. of Images in training set (65)		No. of Images in testing set (36)	
	Normal	Abnormal	Normal	Abnormal
101	**10**	**55**	**4**	**32**

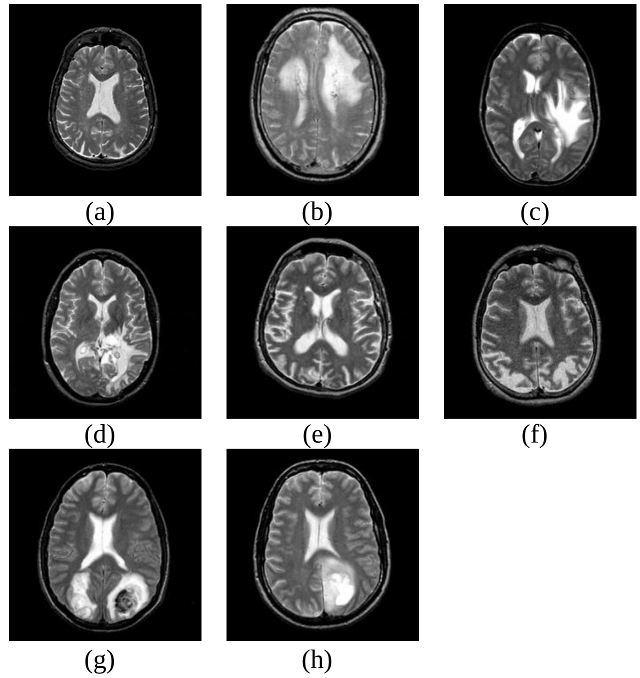

Figure 4. Sample of brain MRI from the database

B. Results

For evaluating the proposed algorithm we used the metrics of sensitivity (measures the proportion of actual positives which are correctly identified), specificity (measures the proportion of negatives which are correctly identified), and accuracy as

$$\text{Sensitivity}=TP/(TP+FN) \tag{8}$$
$$\text{Specificity}=TN/(TN+FP) \tag{9}$$
$$\text{Accuracy}= (TP+TN)/(TP+TN+FP+FN) \tag{10}$$

where: TP: (True Positives) is the correctly classified positive cases, TN: (True Negative) is the correctly classified negative cases, FP: (False Positives) is the incorrectly classified negative cases and FN: (False Negative) is the incorrectly classified positive cases. The experimental results for normal and abnormal classification are listed in Table II.

TABLE II. CLASSIFICATION RATES

TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Acurracy (%)
87	13	1	0	100%	92.8%	99%

The results show that our method obtains quite perfect results on both training and test images. Moreover, for evaluating the effectiveness of the results our method we have made a comparison between the recently published techniques for the brain MRI during the last five years

(2006-2011). Table III shows the classification accuracy comparison.

TABLE III. THE CLASSIFICATION ACCURACY COMPARISON

Approaches	Acurracy (%)	Sensitivity (%)	Specificity (%)
Our proposed method	**99%**	**100%**	**92.8%**
DWT + PCA + BPNN (Zhang et al.) (2011)	**100%**	**100%****	**100%****
SRGS + CCL + DWT + PCA + BPNN (Jafari et al.) (2011)	**99.8%****	**100%**	**98%**
DWT + PCA + K-NN (El-Dahshan et al.) (2010)	**98%**	**96%**	**97%**
DWT + PCA + ANN (El-Dahshan et al.) (2010)	**97%**	**95.9%**	**96%**
DWT + SVM (Chaplot et al.) (2006)	**96%**	*	*
DWT + SVM with radial basis function based kernel (Chaplot et al.) (2006)	**98%**	*	*
DWT + SOM (Chaplot et al.) (2006)	**94%**	*	*

*Unknown Values **Calculated with values of parameters published by the authors for each approach based on the equations (8) - (10).

From table III it can be seen that: (a) Zhang et al. gives the highest accuracy results, (b) Our proposed method, Zhang et al. and Jafari et al. give the highest sensitivity results and (c) Zhang et al. gives the highest specificity results. The highest results given by Zhang et al. is due to selecting a small number of brain MRIs from the dataset (66 images) which couldn't have a lot of varaities and then gave a better results.

IV. CONCLUSIONS

With the advance of computational intelligence and machine learning techniques, Computer-aided detection (CAD) attracts more attention for brain tumor detection. It has become one of the major research subjects in medical imaging and diagnostic radiology. We present a hybrid technique for processing of MRI brain images. This technique first applies feedback pulse-coupled neural network (FPCNN) as a front-end processor for image segmentation and detecting the region of interest (ROI), and then employs the discrete wavelet transform (DWT) to extract features from MRI images. Moreover the principal component analysis (PCA) is performed to reduce the dimensionality of the wavelet coefficients which results in a more efficient and accurate classifier. The reduced features are sent to backpropagation neural network (BPNN) to classify inputs into normal or abnormal based on feature selection parameters. A preliminary evaluation on MRI brain images shows encouraging results, which demonstrates the robustness of the proposed technique.

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